The day-of-the week effects on the volatility: The role of the asymmetry

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THE DAY-OF-THE WEEK EFFECTS ON THE VOLATILITY: THE ROLE OF THE ASYMMETRY.

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Abstract

In this paper, we propose to evaluate whether asymmetry influences the day-of-the-week effects on volatility. We also investigate empirically the impact of the day-of-the-week effect in major international stock markets using GARCH family models from a forecast framework. Indeed the existence of calendar effects might be interesting only if their incorporation in a model results in better volatility forecasts.

Keywords : day-of-the-wekk effects, asymmetry, volatility forecasts

1 Introduction

The day-of-the-week effect is one of the most widely documented seasonal anomalies, according to which stock returns are significantly higher on some days of the week than on other days (Lakonishok and Smidt, 1988; Barone, 1990; Aggarwal and Tandon, 1994). There is an extensive literature on anomalies in financial markets notably examines size effects, stock split effects, and seasonal effects[1]. It is well documented that some predictable patterns exist in the day-of-the-week returns.

Empirical studies have found that the day of the week effect appears not only in the US, which is the biggest capital market in the world, and other developed markets (UK, France, Canada, Australia, Japan), but also in emerging markets (China, Malaysia, Hong Kong, Turkey).

What are the explanations for differences in expected returns across days of the week? Many potential explanations for the weekend effect have been proposed and investigated: measurement errors; delay between trading and settlement in stocks; specialist related biases in prices; spill-over effect from other large markets; concentration of certain investment decisions; timing of corporate releases after Friday's close; reduced institutional trading and greater individual trading on Mondays; country-specific settlement procedures; risk-return tradeoff; daily savings for two weekends a year; speculative short sales; new political macroeconomics and transactions costs. At this point, it should be noted that the above explanations are not fully adequate to explain the phenomenon of the day-of-the-week anomaly. The literature to date does not provide an adequate explanation for this phenomenon. This market anomaly is consequently an intriguing research topic.

These day-of-the-week findings appear to conflict with the efficient market hypothesis since they imply that investors could develop a trading strategy to benefit from these seasonal regularities[2]. Nevertheless, the Monday effect, which is the day-

[1] See for example the recent volume of Keim and Ziemba (2000) for a general discussion.

[2] However, once transaction costs and time-varying stock market risk premiums are taken into account, it is not clear that the predictability of stock returns translates into market inefficiencies.

of-the-week effect most frequently discussed in the literature, has not being of profitable use in trading. The average weekend decline of 0.089 percent found by Siegel (1998) would amount to only 0.0445 US dollars for a 50 US dollars stock which is less than the bid-ask spread that prevailed during the period studied. Many other references make this same point including French (1980), Kim (1988), Bessembinder and Hertzel (1993), Ko and Lee (1993), and Chow *et al.* (1997). Consequently, the only potential for profiting from the day-of-the-week effect through trading individual stocks would be through changing the timing of trades that are already planned, such as timing purchases for Mondays and sales for Fridays in the case of a Monday effect.

Kohers *et al.* (2004) assert that because of improvements in market efficiency over time, the day-of-the-week effect may have disappeared in more recent years. Using both parametric and nonparametric statistical tests, the authors examine the evolution of the day-of-the-week seasonality for the largest developed equity markets over the last 22 years. Their results indicate that while the day-of-the-week effect was clearly prevalent in the vast majority of developed markets during the 1980s, it appears to have faded away starting in the 1990s. These findings imply that increases in market efficiency over long time periods may erode the effects of certain anomalies such as the day-of-the-week effect. *A contrario*, Cho *et al.* (2007) provide a test of the day-of-the-week effect in daily stock index returns based on the stochastic dominance criterion. They apply the test to a number of stock indexes including US large caps and small caps as well as UK and Japanese indexes. They find strong evidence of a Monday effect in many cases under this stronger criterion. The effect has reversed or weakened in the Dow Jones and SP 500 indexes post 1987, but is still strong in more broadly based indexes like the NASDAQ, the Russell 2000 and the CRSP. Consequently, the debate on the existence of seasonal patterns on returns remains open.

For a rational financial decision maker, returns constitute only one part of the decision-making process. Risk-averse investors are interested not only in the variation of their return, but also its volatility. It is important to determine whether there are variations in volatility of stock returns in day-of-the-week patterns and whether a high (low) return is associated with a corresponding high (low) return for a given day. Having such knowledge may allow investors to adjust their portfolios by taking into account day-of-the-week variations in volatility. For example, Engle (1993) argues that investors that dislike risk may adjust their portfolios by reducing their investments in those assets whose volatility is expected to increase. Finding certain patterns in volatility may be useful in several ways, for instance by identifying predicted volatility patterns for hedging and speculative purposes and using predicted volatility to value certain assets, in particular stock index options.

Several authors have investigated the time series behavior of stock prices in terms of volatility using various GARCH models[3]. Balaban *et al.*(2001) use a GJR-GARCH framework to test daily stock returns for 19 countries and find a significant day-of-the-week effect on volatility for 8 countries. Berument and Kiymaz (2001) model the day-of-the-week effect in a GARCH specification by allowing the constant term to vary for each day-of-the-week. The authors show that the day-of-the-week effect is present on the SP 500 index in both the volatility and return equations. Berument *et al.* (2007) assess the day-of-the-week effect on foreign exchange rate changes and their volatility with an EGARCH specification. More recently, Alagidede (2008) investigates the day-of-the-week anomaly in Africa's largest stock markets by looking at both the first and second moments of returns. From a GARCH in mean model, the author incorporates the market risk to test for the presence of daily effects. There is significant daily seasonality for some of African stock markets regarding both mean and variance.

Nevertheless, these empirical studies estimate the day-of-the-week effect in the return and volatility jointly. Therefore, one cannot evaluate whether asymmetry influences the day-of-the-week effect on volatility. Consequently, we propose to determine whether incorporating asymmetric effects of positive and negative shocks on volatility adds a new twist to the existing understanding of the day-of-the-week

[3]See Poon and Granger (2003) for an overview.

effect on volatility. Our aim is to show whether after corrections for the asymmetries, the day-of-the-week effect weakens substantially[4]. Further, we investigate the impact of the day-of-the-week effect in major international stock markets empirically using GARCH family models in a forecast framework. Indeed, as underlined by Balaban *et al.* (2001) and Holden *et al.* (2005), the existence of calendar effects might be interesting only if their incorporation in a model results in better forecasts. Thus, we propose to check whether these seasonal effects are useful for forecasting.

The rest of this paper is organized as follows. Section 2 introduces the data and some preliminary statistical tests. Section 3 specifies the volatility models used. The empirical results are presented in Section 4 and Section 5 concludes.

2 Data and some preliminary statistical tests

The data consist of the daily closing of five international indexes: CAC 40 (France), DAX 30 (Germany), DJIA (US), FTSE 100 (UK) and NIKKEI 225 (Japan). The indexes are basically designed to reflect the largest firms: the CAC 40 is the main French index that is based on 40 of the largest companies in terms of market capitalization; the DAX 30 is the main German indicator of the blue-chip segment and contains the 30 largest companies in terms of capitalization and turnover; the Dow Jones Industrial Average (DJIA) includes 30 of the largest US stocks[5]; The FTSE 100 is the senior index in the UK and consists of the largest 100 UK companies by full market value and the Nikkei 225 Stock Average contains 225 of the most actively traded stocks on the first section of the Tokyo Stock Exchange.

The data cover the period from July 7^{th}, 1987 through July 27^{th}, 2007 for a total of 5205 observations. The daily return is computed as the natural logarithmic first dif-

[4] Chang *et al.* (1998) examined the robustness of day-of-the-week effects on US stock markets. Their results indicate that once the asymmetries are removed, day-of-the-week effects in mean returns are reduced substantially.

[5] The stocks are selected at the discretion of the editors of The Wall Street Journal and add up to about 29% of the US market capitalization. Unlike, most indices the DJIA does not weight the individual stocks by their market capitalization.

ference of the daily closing price. The data are obtained from Thomsom Financial-Datastream.

Tables 1 and 2 report the descriptive statistics for returns for each day-of-the-week and for each market. The first column reports the daily mean, the second provides the standard deviation, the third column reports the skewness, the fourth represents the kurtosis, and the fifth corresponds to the Jarque-Bera statistic. An examination of these characteristics shows that average daily returns are positive for all indexes expect the NIKKEI 225, for which the average daily returns are negative. Monday has the highest variance for all indexes[6]. This phenomenon can be explained by larger volatility on the day following the exchange weekend (French and Roll, 1986). The lowest variance is displayed on Fridays for CAC 40, DAX 30 and NIKKEI 225. Harvey and Huang (1991) argue that the most important US macroeconomic announcements usually are released between 8:30 and 9:30 a.m. on Fridays, which induce higher volatility. Their results do not necessarily conflict with ours because these announcements are likely to mainly affect opening price. Because we are using closing price, the impact on volatility should lessen by the end of Friday's trading. DJIA and FTSE 100 indexes display the lowest variance on Wednesday. The highest average returns are observed on Mondays for the DJIA; on Thursdays for CAC 40 and NIKKEI 225 and on Fridays for DAX 30 and FTSE 100. The lowest average returns are on Mondays for CAC 40, FTSE 100 and NIKKEI 225 with a negative sign; on Tuesdays for DAX 30 with a positive sign and on Thursdays for DJIA with a negative sign.

Tables 1 and 2 also report skewness and kurtosis for the return series of each market. All sample distributions are negatively skewed, indicating that they are non symmetric. Furthermore, they all exhibit high levels of kurtosis, indicating that these distributions have thicker tails than normal distributions. These initial findings show that

[6]Kyimaz and Berument (2003) have shown that for Germany and Japan, the days with the highest volatility also coincide with that market's lowest trading volume.

daily returns are not normally distributed; they are leptokurtic and skewed.

We now test for constancy of variance prior to comparing the mean across different days. Indeed, the choice of test of comparison of mean depends on whether the variance is homogenous across different days. We further perform Brown-Forsythe test (Brown and Forsythe, 1974) to see whether the constancy of the variances across the days of the week can be rejected. Brown-Forsythe test is used to determine whether k samples have equal variance. Brown-Forsythe test is more robust to departure from normality, an assumption that is strongly rejected in our data[7].

The results are reported in Table 3. By applying Brown-Forsythe test, the hypothesis that variance is constant across the days of the week is rejected for all series except for the FTSE 100 index. As we have shown that the variance is not constant over time (except for the FTSE 100 series) and the series are non-normal, we use the Kruskal-Wallis test to examine the existence of the day-of- the-week effect in the world's developed equity markets. We reject the null hypothesis that the mean is constant over the week for all series except for the DJIA index, which shows a day-of-the-week effect on returns.

3 Modelling the day-of-the-week effect on volatility

Finding patterns in volatility may be useful in several ways, including identifying volatility patterns for hedging and speculative purposes and the use of predicted volatility in valuation of certain assets specifically stock index options. Furthermore, investors may adjust their portfolios by reducing their commitments to assets whose

[7] There are numerous tests for equal variances, but, as by Box (1953) points out, many of them appear to be sensitive to departures from normality, outliers and heteroskedasticity. Several tests have been proposed to deal with this problem. Conover *et al.* (1981) list and compare 60 methods for testing the homogeneity of variance assumptions and show that Brown-Forsythe procedure outperforms all the other procedures. Moreover, Brown and Forsythe (1974) performed Monte Carlo studies that indicated that using the trimmed mean performed best when the underlying data followed a heavy-tailed distribution and the median performed best when the underlying data followed a skewed distribution.

volatility is expected to increase, and vice versa.

3.1 The GARCH and GJR-GARCH models

The GARCH model, developed by Bollerslev (1986), has been a major tool in modelling predictability and time variation in the volatility of financial asset returns (Hansen and Lunde, 2005). In this context, the estimated volatility is symmetric; i.e. the forecast errors, whether positive or negative, have the same effect on the conditional volatility. However, it is well documented in the literature that negative shocks may have a different effect on volatility (Black, 1976). For example, according to the so-called leverage effect, negative shocks increase volatility more than positive shocks of equal magnitude do. Several volatility models have been developed to take non-symmetrical dependencies into account[8]. In this paper, we consider only the first generation threshold models[9] such as the GJR-GARCH (Glosten *et al.*, 1993) and APARCH models (Ding *et al.*, 1993).

One very simple method for examining the degree to which seasonality is present in the financial time series is the inclusion of dummy variables in regression equations[10]. We consider the following model

$$R_{it} \quad = \quad \mu_0 + \sum_{i=1}^{p} \phi_i R_{t-i} + \sum_{j=1}^{q} \theta_i \varepsilon_{t-j} + \sum_{k=1}^{4} \lambda_k D_{kt} + \varepsilon_t$$

where R_{it} represents the returns of the index i at time t, $\varepsilon_t = z_t\sigma_t, \varepsilon_t \sim N(0, \sigma_t^2)$ and $z_t \sim i.i.d.N(0,1)$ and the conditional variance of ε_t is given by

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + + \gamma \varepsilon_{t-1}^2 I_{t-1} + \sum_{k=1}^{4} \delta_k D_{kt}$$

The parameters should satisfy $\alpha_0 > 0$, $\alpha_1 \geq 0$ and $\beta_1 \geq 0$ to guarantee the positivity of the conditional variance ($h_t \geq 0$). If there are no asymmetries, γ is not statistically

[8] See Li and Li (1996), Brooks (2001), Chen *et al.* (2006), Munõz *et al.* (2007) and Chen *et al.* (2008).

[9] For a review of those models see Franses and van Dijk (2000) and the references contained therein.

[10] An alternative way to model seasonality in stock returns is the periodic autoregressive model with periodic integrated GARCH process proposed by Franses and Paap (2000) and the periodic stochastic volatility process developed by Tsiakas (2006).

significant and the previous volatility equation is the equation of a GARCH model. D_{kt} is a binary variable such that $D_{1t} = 1$ if day t is a Monday and 0 otherwise; $D_{2t} = 1$ if day t is a Tuesday; $D_{3t} = 1$ if day t is a Wednesday and $D_{4t} = 1$ if day t is a Thursday. We exclude the dummy variable for Friday to avoid the dummy variable trap[11]. Care needs to be taken with dummy variables in variance equation so that negative effect estimates do not lead to negative variances. As no restrictions are placed on the dummy effects, it is necessary to check that the variance and the forecasted variance are positive[12].

3.2 The Asymmetric Power ARCH model

Since the introduction of the ARCH/GARCH family of models, many additional features have been added to the base models to capture more complex volatility dynamics. These additional features include leverage and asymmetry effects and power transformations. A popular general model that captures these two features is the Asymmetric Power ARCH [APARCH] model introduced by Ding *et al.* (1993). Indeed, this model nests at least seven ARCH-type models (see below) and was found to be particularly relevant in many recent applications (Mittnik and Paolella, 2000; Giot and Laurent, 2003; Huang and Lin, 2004; Brooks, 2007). The APARCH(p,q) model can be expressed as

$$R_t = \mu_0 + \sum_{i=1}^{p} \phi_i R_{t-i} + \sum_{j=1}^{q} \theta_i \varepsilon_{t-j} + \sum_{k=1}^{4} \lambda_k D_{kt} + \varepsilon_t$$

where $\varepsilon_t = z_t \sigma_t, \varepsilon_t \sim N(0, \sigma_t^2)$ and $z_t \sim i.i.d.N(0,1)$ and the conditional variance of ε_t is given by

$$\sigma_t^{\upsilon} = \alpha_0 + \sum_{i=1}^{q} \alpha_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^{\upsilon} + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

where $\alpha_0 > 0, \upsilon \geq 0, \beta_j \geq 0 (j = 1, ..., p), \alpha_i \geq 0$ and $-1 < \gamma_i < 1 (i = 1, ..., q)$. The asymmetry in the model is captured via the parameter γ_i and the power term υ captures both the conditional standard deviation (υ=1) and conditional variance (υ=2) as special

[11] The dummy variable effect estimates are all in comparison to the base level of Friday.

[12] We thank one referee for this important insight.

cases. This model is quite interesting because it couples the flexibility of a varying exponent with the asymmetry coefficient (to take the leverage effect into account). Moreover, the APARCH includes seven other ARCH extensions as special cases[13]:

- ARCH when $\upsilon = 2$, $\gamma_i = 0$ (i=1,...,p) and $\beta_j = 0$ (j=1,...,q)
- GARCH when $\upsilon = 2$ and $\gamma_i = 0$ (i=1,...,p) $\beta_j = 0$ (j=1,...,q)
- the GARCH of Taylor (1986) and Schwert (1990), when $\upsilon = 1$ and $\gamma_i = 0$ (i=1,...,p)
- GJR-GARCH when $\upsilon = 2$
- the Threshold ARCH of Zakoian (1994), when $\upsilon = 1$
- the Nonlinear ARCH of Higgins and Bera (1992), when $\gamma_i = 0$ (i=1,...,p) and $\beta_j = 0$ (j=1,...,q)
- the log-ARCH of Geweke (1986) and Pentula (1986), when $\upsilon \longrightarrow 0$

The parameters in the previous volatility models can be estimated[14] by maximizing the log likelihood corresponding with the conditional normality of ε_t. As one can never be sure that the specified distribution of z_t is the correct one, an alternative approach is to ignore the problem and base the likelihood on the normal distribution. This method is referred to a quasi-maximum likelihood estimation (QMLE). In general, the resulting estimates remain consistent and asymptotically normal, provided that the models for the conditional mean and the conditional variance are correctly specified. The iterative optimization procedures can be used to estimate the parameters. More precisely, it is necessary to solve the first and second-order derivatives of the log likelihood (LL) from several algorithms such as the score or the Hessian matrix. The most popular algorithm for estimating GARCH models is that of Berndt *et al.* (1974) [BHHH][15].

[13]Complete developments leading to these conclusions are available in Ding *et al.* (1993).

[14]To estimate and forecast these indexes, we use G@RCH 4.2 of Laurent and Peters (2001), a package dedicated to the estimation and the forecasting of GARCH models and many of theirs extensions.

[15]BHHH employ only first derivatives (calculated numerically rather than analytically) and approximations to the second derivatives are calculated.

The QMLE enables the rate of returns and variance processes to be estimated jointly.

4 Empirical results

We first estimate an ARMA model for each return series to remove any serial correlation in the series[16]. We employ the Ljung-Box [LB] test for autocorrelation (Ljung and Box, 1978), the Lagrange Multiplier [LM] test for homoskedasticity (Engle, 1982) and the BDS test statistic for non-linearity (Brock, Dechert and Scheinkman, 1987). The LB statistic is not significant for all series, meaning that there is no serial linear correlation on the return series. The data exhibit conditional heteroskedasticity given that the LM test is significant for all series. Finally, to test for general non-linearity we apply the most widely used test: the BDS test. We observe that all the series display nonlinearity. The latter two results confirm the leptokurticity of the return distributions observed previously.

In general, the empirical studies (Kiymaz and Berument, 2003; Alagidede, 2008) estimate the day-of-the-week effect in the return and volatility jointly. Therefore, one cannot evaluate how asymmetry influences the day-of-the-week effect on either return or volatility[17]. Consequently, we have chosen to model the return series with an appropriate model before taking into account the presence of the day-of-the-week effect on return and volatility. This procedure is employed to determine whether incorporating asymmetric effects on volatility adds a new twist to the understanding of the day-of-the-week effect on volatility.

In Table 4, we report the estimates of ARMA-GARCH models[18] without seasonal

[16]The results are not reported to save space but they are available from the authors upon request.

[17]We thank a referee for this important insight.

[18]Mispecification of the conditional mean equation appears to have very little influence on the estimated conditional variance in continuous (Nelson, 1990a; 1990b) as well as discrete time (McKenzie, 1997).

effects for each series to take into account only the previously detected conditional heteroskedasticity. To check the adequacy of a time series model for the conditional mean and the conditional variance, we compute a number of misspecification tests[19]. The mean equation seems adequate because the LB test up to 10 is not significant for all series. The LM test up to 10 is not significant, revealing that no further ARCH effects are detected. The Nyblom test is used to check the constancy of parameters over time. This test is an approximate LM test of the null hypothesis that the parameter is constant versus the alternative hypothesis, a martingale process[20]. The Nyblom stability test suggests that the estimated parameters are quite stable during the investigated period, implying that this model may be used to forecast volatility. Finally, we test a linear GARCH specification relative to nonlinear alternatives by means of the joint test developed by Engle and Ng (1993). This test serves to determine whether an asymmetric model is required for a given series, or whether the symmetric GARCH model can be deemed adequate. There is substantial evidence of asymmetric ARCH effects at 5% for all series except the FTSE 100. Nevertheless, the rejection of the null hypothesis by the test does not give much information concerning which nonlinear GARCH model might be the appropriate alternative.

To take into account the asymmetry detected on the GARCH residuals, we estimate an ARMA-GJR-GARCH model without seasonal effects. The estimate for each series is reported in Table 5. The asymmetric effect is present in all markets, which means that negative shocks have a greater impact on this market than positive shocks do. The diagnostic tests of the standardized residuals[21] indicate that the LB(10) statistics are not statistically significant. Thus, we conclude that the residuals are not autocorrelated. In addition, the LM(10) tests cannot reject the null hypothesis of no ARCH effects for all countries. As the Engle-Ng test is significant at 5% for all series, we may ask whether the hypothetical day-of-the-week effects on volatility do not create

[19]The results are not reported to save space but they are available from the author upon request.

[20]See Nyblom (1989), Lee and Hansen (1994) and Hansen (1994).

[21]The results are not reported to save space but they are available from the author upon request.

asymmetry in the data[22]. Another nonlinear GARCH model or a model that captures the seasonal effects might be an appropriate alternative.

Finally, we estimate an APARCH model to capture the leverage effect. The results are presented in Table 6. All coefficients are significant at 5%. The asymmetry is observed through the γ coefficient. All misspecification tests[23] are not significant, except the asymmetry test, which is significant except for the CAC 40, DAX 30 and DJIA series.

In Section 2 we have detected the presence of the day-of-the-week effect on volatility for all series but on returns only for the DJIA index. Consequently, we tried to model these effects using the previous models and the methodology presented in Section 3. Results are reported in Tables 7 and 9. We note that, regardless of the volatility models used, all coefficients are significant, implying the presence of asymmetry in the volatility equation but also the existence of seasonal effects in the mean and variance equations. Indeed, the day-of-the-week effects on volatility are detected on Mondays, Tuesdays and Thursdays for the DAX 30; and on Mondays and Thursdays for the DJIA for all seasonal volatility models estimated. Nevertheless, we observe some differences between the estimates of the volatility models and particularly on the detected seasonal effects for the other indexes. When we consider the ARMA-GJR-GARCH models with dummies exclusively, we may conclude that there are no day-of-the-week effects on volatility of the CAC 40. However, when we estimate an ARMA-APARCH with dummies, for the same series, the results are quite different. Indeed, we note one day-of-the-week effect on Mondays and one on Tuesdays. There is also a substantial difference in the estimates for the NIKKEI 225. Indeed, a Tuesday effect is detected on volatility with ARMA-GJR-GARCH models with dummies, whereas we observed Tuesday and Monday effects when we estimate the series with an ARMA-APARCH

[22]It would be interesting to study the impact of seasonal effects on the asymmetry tests from Monte Carlo simulations in further research.

[23]The results are not reported to save space but they are available from the author upon request.

with dummies. Thus, the choice of the volatility model seems very important to detect the day-of-the-week effects on volatility because the results may differ depending on the model. An inappropriate asymmetric volatility model may lead to a misspecification of the seasonal effects. Nevertheless, when we compare the LL criterion, it appears that it is highest when an ARMA-APARCH is estimated. Consequently, this model seems to best capture the characteristics of the financial series used in this study. Thus, for the FTSE 100, seasonal effects on Mondays and Tuesdays are detected, yet in this series no conditional asymmetry on volatility has been detected with the Engle-Ng test.

The diagnostic tests on the standardized residuals of these two seasonal volatility models are shown in Tables 8 and 10. No ARCH effects or autocorrelation have been detected. According to the Nyblom test, the coefficients are stable over time, which is an important result for the forecast framework. Finally, the asymmetry seems to be well taken into account because the Engle-Ng test is not significant for all series. Thus we can advance that the seasonal effects may create asymmetry. Indeed, when the seasonal pattern is not taken into account on volatility process, the asymmetric conditional volatility test is significant. An alternative solution will be to use an asymmetric distribution as proposed by Baker *et al.* (2007)[24]. Contrary to these authors, the day-of-the-week effect in both mean and conditional variance is not sensitive to the distribution assumption. Indeed, such distributions don't improve the estimates and the diagnostic tests on residuals[25]. Consequently, the seasonal effects can be view as an alternative to model the asymmetry on the conditional variance. The seasonal effect modelling allows to capture the asymmetry on the conditional variance.

[24]In this study, we have used the Student and the GED distributions, or the more recent Skewed-Student distribution.

[25]The results of these estimates are not reported because they are not significant but they are available from the author upon request.

5 Volatility forecasts

In a recent review article, Poon and Granger (2003) present a persuasive case for why the forecasting of volatility is a critical activity in financial markets. Volatility forecasts have a very wide sphere of influence including investment, security valuation, risk management, and monetary policy making. Specifically, they emphasize the importance of volatility forecasting in: (*i*) pricing of options, underlined by the recent massive growth in the trading of derivative securities; (*ii*) financial risk management in the global banking sector, stimulated by the Basel Accords; and (*iii*) US monetary policy, especially in the wake of major world events such as September 11th.

To simplify the reading of the forecast framework, we use the following notations

- Model 1: ARMA-GARCH without dummies
- Model 2: ARMA-GJR-GARCH without dummies
- Model 3: ARMA-APARCH without dummies
- Model 4: ARMA-GJR-GARCH with dummies
- Model 5: ARMA-APARCH with dummies

We estimate model 1 to model 5 for each series in the in-sample estimation period (4965 observations). The fitted models are used to obtain one-step ahead forecasts of conditional variance. The estimation is then moved one day into the future, by deleting the first observation and adding one observation. The various GARCH models are re-estimated on this new sample and are used to obtain one-step ahead volatility forecasts. In this way, we obtain 240 one-step ahead forecasts of the conditional variance.

The fact that the measures of volatility are latent makes it difficult to evaluate the performance of volatility models. A common solution to this problem is to substitute a proxy for the true volatility and evaluate the models by comparing their predicted volatility to the proxy. Nevertheless, the use of a conditionally unbiased, but imperfect, volatility proxy can lead to undesirable estimates in standard methods for comparing conditional variance forecasts. Alizadeh *et al.* (2002) note that the log range, defined as the log of the difference between the high and low log prices during the day, is a better measure of volatility in the sense that the log range has fewer measurement errors compared with squared-returns. For instance, on a given day, the price of an asset fluctuates substantially throughout the day but its closing price happens to be very close to the previous closing price. If we use the inter-daily squared return, the value will be low despite the large intra-daily price fluctuations. The log range, using the highest and lowest values, reflects more precise price fluctuations and can indicate that the volatility for the day is high. The log range has the advantage of being robust to certain market microstructure effects. These microstructure effects, such as the bid-ask spread, are noise that can affect the features of the time series. Moreover, the distribution of the log range is very close to Normal, which makes it attractive for use in Gaussian QMLE models. Nevertheless, it has been recognized at least since Taylor (1986) and Ding *et al.* (1993) that absolute returns show more persistence than squared returns. More specifically, it is well known that the persistence of volatility measures based on squared returns fades even more, whereas the absolute returns are immune to the presence of jumps (Forsberg and Ghysels, 2007). Therefore, in this study, we consider two volatility proxies: the log absolute return $ln|R_{it}|$ and the log range $ln|\sup p_t - \inf p_{it}|$ where R_{it} represents the returns of the index i at time t and, p_t the closing daily price of the index i at time t.

It is difficult to compare the forecasting performance of competing models because of the diverse evaluation criteria used in the literature. In essence statistical measures evaluate the difference between forecasts at time t and realized values at time $t+h$. It is possible to test the null hypothesis that there is no qualitative difference between the forecasts based on two models by comparing predictive accuracy. Diebold and Mariano (1995) [DM] proposed tests for equal accuracy between two forecasting models based on squared and absolute forecast errors. The null hypothesis is the equal predictive accuracy of the two models. The results are reported on Tables 11 and 12.

The DM statistics are, in most cases, significant, meaning there is a difference in the forecasts computed from the two volatility models used. A positive sign of the statistics implies that model 2 (GJR-GARCH without dummies) or 3 (APARCH without dummies) is dominated by model 4 (GJR-GARCH without dummies) or 5 (APARCH without dummies), respectively. A negative sign of the statistics implies that model 2 (GJR-GARCH without dummies) or 3 (APARCH without dummies) dominates model 4 (GJR-GARCH without dummies) or 5 (APARCH without dummies), respectively.

The results indicate that the day-of-the-week effects detected on volatility do not seem to improve the volatility forecasts. Indeed, the sign of the DM statistics is negative, implying that the day-of-the week effects observed on volatility do not provide a better volatility forecast. Note that the volatility forecasts of the FTSE 100 have been computed from a GARCH model (with and without dummies) given that the Engle-Ng test was not significant. Consequently, the day-of-the-week effects detected on volatility may be regarded as something that cannot be traded profitably.

6 Conclusion

The previous empirical studies that have investigated the day-of-the-week effect on volatility from a GARCH framework mainly estimated the seasonal effects and the volatility jointly. Therefore, one cannot evaluate whether asymmetry influences the day-of-the-week effect on volatility. Consequently, we propose to determine whether incorporating asymmetric effects of positive and negative shocks on volatility adds a new twist to the existing understanding of the day-of-the-week effect on volatility. First, we show that the choice of the volatility model seems to play an important role in detecting the day-of-the-week effects on volatility because the results differ depending on the model used. Second, the asymmetry does not seem to influence the seasonal effects. *A contrario*, it is possible that the day-of-the-week effect creates asymmetry in the series. Third, we investigate the impact of the day-of-the-week effect in major international stock markets empirically using GARCH family models in a forecast framework. Indeed, the existence of calendar effects might be interesting only if their incorporation in a model results in better volatility forecasts. In this case, investors could develop a trading strategy to benefit from these seasonal regularities. Our results indicate that the day-of-the-week effects detected on volatility do not seem to improve the volatility forecasts, implying that it is not worth integrating these effects in trading strategies.

Table 1: Summary statistics of daily closing prices

CAC 40					
Weekday	Mean	Std. Deviation	Skewness	Kurtosis	JB
Monday	-0.000691	0.014393	-0.795224**	9.231824**	1794.214**
Tuesday	0.000372	0.012491	-0.306796**	7.808605**	1019.277**
Wednesday	0.000080	0.012440	-0.439254**	6.867420**	682.2331**
Thursday	0.000891	0.013541	0.266541**	6.912407**	676.2641**
Friday	0.000689	0.011725	0.077335	5.831395**	348.7662**
All days	0.000268	0.012959	-0.288916**	7.834683**	5141.683**
DAX 30					
Weekday	Mean	Std. Deviation	Skewness	Kurtosis	JB
Monday	0.000295	0.016368	-1.105457**	12.34201**	2997.494**
Tuesday	0.000146	0.013559	-0.573542**	9.368490**	1816.262**
Wednesday	0.000360	0.013343	-0.140672**	5.732799**	327.3661**
Thursday	0.000352	0.013588	0.054833	7.993921**	1082.262**
Friday	0.000502	0.012994	-0.227433**	7.036659**	715.7524**
All days	0.000331	0.014019	-0.506888**	9.611611**	9703.235**
DJIA					
Weekday	Mean	Std. Deviation	Skewness	Kurtosis	JB
Monday	0.000688	0.013246	-7.678206**	142.2678**	851509.2**
Tuesday	0.000595	0.009897	0.395145**	6.758283**	639.7487**
Wednesday	0.000551	0.009597	1.168749**	14.86838**	6346.733**
Thursday	-0.000180	0.009932	-0.018083	6.775010**	618.1807**
Friday	-0.000033	0.010209	-1.085942**	9.640348**	2117.190**
All days	0.000324	0.010664	-2.887988**	72.87770**	1066213**

** means significant at the 5% level.

Table 2: Summary statistics of daily closing prices

FTSE 100					
Weekday	Mean	Std. Deviation	Skewness	Kurtosis	JB
Monday	-0.000292	0.010951	-1.494095**	17.75499**	9830.463**
Tuesday	0.000223	0.010629	-1.950180**	25.59618**	24810.18**
Wednesday	0.000043	0.009647	0.212018**	8.398238**	1271.789**
Thursday	0.000369	0.010299	-0.092353	7.212007**	770.9958**
Friday	0.000662	0.009765	-0.035891	5.882543**	360.6288**
All days	0.000201	0.010271	-0.788386**	14.45900**	29016.79**

NIKKEI 225					
Weekday	Mean	Std. Deviation	Skewness	Kurtosis	JB
Monday	-0.000943	0.015383	-0.147147**	5.991917**	392.0308**
Tuesday	0.000331	0.013759	-0.907874**	27.31375**	25784.50**
Wednesday	0.000152	0.013880	0.398066**	6.866685**	676.0027**
Thursday	0.000393	0.013186	-0.074859	5.195281**	210.0076**
Friday	-0.000204	0.013035	0.240771**	6.477068**	534.4616**
All days	-0.000054	0.013877	-0.120415	10.30315**	11 579.81**

** means significant at the 5% level.

Table 3: Tests for equality

Tests for equality of variance					
Brown-Forsythe's test					
	CAC 40	DAX 30	DJIA	FTSE 100	NIKKEI 225
p-value	0.02^{**}	0.00^{*}	0.00^{*}	0.93	0.00^{*}
Test for equality of mean					
Kruskal Wallis's test					
	CAC 40	DAX 30	DJIA	FTSE 100	NIKKEI 225
p-value	0.30	0.92	0.02^{**}	0.22	0.40

* and ** means significant at the 1% and 5% levels, respectively.

Table 4: Estimates of ARMA-GARCH model

	CAC40	DAX 30	DJIA	FTSE 100	NIKKEI 225
Mean equation					
μ_0	0.54^{*} (0.00)	0.72^{*} (0.00)	0.57^{*} (0.00)	0.04^{*} (0.00)	0.05^{*} (0.00)
ϕ_1	-	0.90^{*} (0.00)	0.89^{*} (0.00)	-	-0.95^{*} (0.00)
θ_1	0.02^{***} (0.08)	-0.90^{*} (0.00)	0.71^{*} (0.00)	-	0.96^{*} (0.00)
Variance equation					
α_0	3.18^{*} (0.00)	4.32^{*} (0.00)	1.50^{**} (0.02)	0.01^{*} (0.00)	0.02^{**} (0.04)
α_1	0.08^{*} (0.00)	0.10^{*} (0.00)	0.08^{*} (0.00)	0.08^{*} (0.00)	0.11^{*} (0.00)
β_1	0.89^{*} (0.00)	0.87^{*} (0.00)	0.90^{*} (0.00)	0.89^{*} (0.00)	0.87^{*} (0.00)

Significance at the 1%, 5% and 10% levels is shown by *, ** and ***, respectively. The p-values are given in parentheses.

Table 5: Estimates of ARMA-GJR-GARCH model

	CAC40	DAX 30	DJIA	NIKKEI 225
		Mean equation		
μ_0	0.27^{***} (0.08)	0.41^{**} (0.01)	0.31^{**} (0.01)	$1.03E-06$ (0.55)
ϕ_1	-	0.51^{*} (0.00)	-0.60^{*} (0.00)	0.90^{*} (0.00)
θ_1	0.02^{***} (0.09)	-0.50^{**} (0.01)	0.62^{*} (0.00)	-0.88^{*} (0.00)
		Variance equation		
α_0	3.22^{*} (0.00)	4.62^{*} (0.00)	1.82^{*} (0.00)	$3.05E-06^{*}$ (0.00)
α_1	0.02^{*} (0.02)	0.02^{**} (0.03)	0.01^{***} (0.08)	0.03^{*} (0.00)
β	0.91^{*} (0.00)	0.88^{*} (0.00)	0.91^{*} (0.00)	0.88^{*} (0.00)
γ	0.09^{*} (0.00)	0.12^{*} (0.00)	0.11^{*} (0.00)	0.16^{*} (0.00)

Significance at the 1%, 5% and 10% levels is shown by *, ** and ***, respectively. The *p*-values are given in parentheses. *LL* means the Log Likelihood.

Table 6: Estimates of ARMA-APARCH model

	CAC40	DAX 30	DJIA	NIKKEI 225
		Mean equation		
μ_0	0.27^{***} (0.08)	0.37^{**} (0.02)	0.29^{**} (0.02)	$-2.25E-06$ (0.11)
ϕ_1	-	0.60^{*} (0.00)	-0.59^{**} (0.05)	0.92^{*} (0.05)
θ_1	0.02 (0.11)	-0.59^{*} (0.00)	0.61^{**} (0.03)	-0.90^{*} (0.03)
		Variance equation		
α_0	0.86 (0.17)	0.89 (0.12)	0.24^{**} (0.02)	0.03^{*} (0.00)
α_1	0.06^{*} (0.00)	0.08^{*} (0.00)	0.06^{*} (0.00)	0.09^{*} (0.00)
β	0.92^{*} (0.00)	0.90^{*} (0.00)	0.92^{*} (0.00)	0.89^{*} (0.00)
γ	0.52^{*} (0.00)	0.51^{*} (0.00)	0.84^{*} (0.00)	0.57^{*} (0.00)
υ	1.48^{*} (0.00)	1.43 (0.00)	1.11^{*} (0.00)	1.43^{*} (0.00)

Significance at the 1%, 5% and 10% levels is shown by *, ** and ***, respectively. The p-values are given in parentheses.

Table 7: Estimates of ARMA-GJR-GARCH model with dummies

	CAC40	DAX 30	DJIA	FTSE 100	NIKKEI 225
			Mean equation		
μ_0	0.29^{**} (0.04)	0.41^{*} (0.00)	0.31^{*} (0.00)	0.04^{*} (0.00)	$9.84E-03$ (0.59)
ϕ_1	-	0.58^{**} (0.02)	-0.52^{***} (0.05)	-	-0.98^{*} (0.00)
θ_1	-0.67^{*} (0.00)	-0.57^{**} (0.04)	0.54^{**} (0.04)	0.98^{*} (0.00)	
λ_1	-	-	0.51^{**} (0.02)	-	-
λ_4	-	-	-0.35^{***} (0.09)	-	-
			Variance equation		
α_0	3.29^{*} (0.00)	4.42^{*} (0.00)	1.77^{*} (0.00)	0.02^{*} (0.00)	0.03^{*} (0.00)
α_1	0.02^{*} (0.03)	0.04^{*} (0.00)	0.01^{***} (0.06)	0.08^{*} (0.00)	0.04^{**} (0.03)
β_1	0.91^{*} (0.00)	0.89^{*} (0.00)	0.91^{*} (0.00)	0.89^{*} (0.00)	0.88^{*} (0.00)
γ	0.09^{*} (0.00)	0.10^{*} (0.00)	0.11^{*} (0.00)	-	0.14^{*} (0.00)
δ_1	23.16 (0.17)	49.31^{***} (0.07)	-18.85^{**} (0.04)	0.05^{**} (0.02)	0.45^{*} (0.00)
δ_2	-23.53 (0.15)	-51.57^{**} (0.04)	6.26 (0.21)	-0.08^{*} (0.04)	-0.28^{**} (0.03)
δ_3	2.64 (0.68)	3.94 (0.51)	-10.44^{**} (0.02)	0.01 (0.51)	-0.05 (0.58)
δ_4	5.50 (0.37)	-13.52^{**} (0.05)	3.83 (0.27)	-0.02 (0.39)	$2.58E-03$ (0.98)

Significance at the 1%, 5% and 10% levels is shown by *, ** and ***, respectively. The p-values are given in parentheses. Note that we estimate a ARMA-GARCH model with dummies for FTSE 100 series.

Table 8: Diagnostic tests on residuals of ARMA-GJR-GARCH with dummies

	CAC40	DAX 30	DJIA	FTSE 100	NIKKEI 225
LL	-19999.43	-20175.58	-18723.53	-6745.70	-8437.13
$LB(10)$	11.42 (0.25)	10.96 (0.20)	5.35 (0.72)	12.75 (0.24)	6.02 (0.64)
$LM(10)$	0.87 (0.56)	0.38 (0.96)	0.85 (0.58)	1.26 (0.25)	0.40 (0.95)
JT	5.89 (0.13)	6.12 (0.11)	16.54*** (0.09)	5.00 (0.17)	6.14 (0.10)
Nyblom's test					
α_1	0.37	0.29	0.34	0.16	0.11
β_1	0.40	0.32	0.29	0.20	0.49
γ	0.29	0.29	0.24	-	0.08
δ_1	0.40	0.10	0.50	0.21	0.60
δ_2	0.20	0.42	0.66	0.81	0.23
δ_3	0.04	0.34	0.41	0.36	0.14
δ_4	0.04	0.49	0.18	0.17	0.22

Significance at the 1%, 5% and 10% levels is shown by *, ** and ***, respectively. The p-values are given in parentheses. LL means the Log Likelihood. The LB and LM tests follow a χ^2 distribution with $10-p-q$ and 10 degrees of freedom under the null hypothesis of no autocorrelation and homoskedasticity, respectively. JT represents the joint test of Engle and Ng (1993). It follows a χ^2 distribution with 3 degrees of freedom under the null hypothesis of no asymmetric effects in the volatility. We, only, report the p-values for these two tests. We report only the p-values for the Nyblom's test. The Asymptotic 1% (5%) critical value for individual statistics of this test is 0.75 (0.47).

Table 9: Estimates of ARMA-APARCH model with dummies

	CAC40	DAX 30	DJIA	NIKKEI 225
Mean equation				
μ_0	0.33^{**} (0.03)	0.40^{*} (0.01)	0.29^{**} (0.01)	-0.01 (0.55)
ϕ_1	-	-	-	0.97^{*} (0.00)
θ_1	0.02^{***} (0.09)	-	-	-0.99^{*} (0.00)
λ_1	-	-	0.65^{*} (0.00)	-
λ_4	-	-	-0.43^{*} (0.04)	-
Variance equation				
α_0	0.67^{*} (0.00)	0.88^{*} (0.00)	0.26^{*} (0.00)	0.03^{*} (0.00)
α_1	0.06^{*} (0.00)	0.08^{*} (0.00)	0.06^{*} (0.00)	0.10^{*} (0.00)
β_1	0.92^{*} (0.00)	0.90^{*} (0.00)	0.93^{*} (0.00)	0.89^{*} (0.00)
γ	0.53^{*} (0.00)	0.42^{*} (0.00)	0.83^{*} (0.00)	0.49^{*} (0.00)
υ	1.38^{*} (0.00)	1.39 (0.00)	1.16^{*} (0.00)	1.46^{*} (0.00)
δ_1	4.70^{*} (0.00)	8.84^{*} (0.00)	-1.51^{*} (0.00)	0.34^{*} (0.00)
δ_2	-4.68^{*} (0.00)	-9.33^{*} (0.00)	0.31 (0.30)	-0.18^{**} (0.06)
δ_3	0.59 (0.48)	0.91 (0.29)	-1.16^{*} (0.00)	-0.07 (0.50)
δ_4	0.96 (0.48)	-2.38^{**} (0.01)	0.56^{***} (0.07)	0.00 (0.99)

Significance at the 1%, 5% and 10% levels is shown by *, ** and ***, respectively. The *p*-values are given in parentheses.

Table 10: Diagnostic tests on residuals of ARMA-APARCH model with dummies

	CAC40	DAX 30	DJIA	NIKKEI 225
LL	-19997.85	-20166.92	-18703.23	-8430.17
$LB(10)$	11.79 (0.23)	10.61 (0.22)	5.81 (0.68)	6.08 (0.638)
$LM(10)$	0.88 (0.55)	0.48 (0.91)	1.01 (0.428)	0.37 (0.958)
JT	6.45 (0.10)	4.66 (0.17)	6.33 (0.12)	4.73 (0.19)
		Nyblom's test		
α_1	0.32	0.19	0.47	0.04
β_1	0.36	0.18	0.57	0.32
γ	0.14	0.17	0.13	0.58
υ	0.53	0.29	0.45	0.03
δ_1	0.37	0.16	0.48	0.57
δ_2	0.29	0.47	0.63	0.22
δ_3	0.04	0.42	0.50	0.23
δ_4	0.05	0.64	0.15	0.28

Significance at the 1%, 5% and 10% levels is shown by *, ** and ***, respectively. The p-values are given in parentheses. LL means the Log Likelihood. The LB and LM tests follow a χ^2 distribution with $10-p-q$ and 10 degrees of freedom under the null hypothesis of no autocorrelation and homoskedasticity, respectively. JT represents the joint test of Engle and Ng (1993). It follows a χ^2 distribution with 3 degrees of freedom under the null hypothesis of no asymmetric effects in the volatility. We report only the p-values for the Nyblom's test. The Asymptotic 1% (5%) critical value for individual statistics of this test is 0.75 (0.47).

Table 11: Tests of equal accuracy: Model 2 versus Model 4

	Asymptotic test	Sign test	Wilcoxon test	Asymptotic test	Sign test	Wilcoxon test
Proxy: log absolute returns						
	based on squared forecast errors			based on absolute forecast errors		
CAC 40	0.31 (0.76)	-1.55 (0.12)	-1.95^{***} (0.05)	-0.29 (0.77)	-1.55 (0.12)	-1.75^{***} (0.08)
DAX 30	-3.21^{*} (0.00)	-9.30^{*} (0.00)	-3.89^{*} (0.00)	-0.44 (0.66)	-9.29^{*} (0.00)	-3.77^{*} (0.00)
DJIA	-3.80^{*} (0.00)	-8.65^{*} (0.00)	-3.77^{*} (0.00)	-6.04^{*} (0.00)	-8.65^{*} (0.00)	-3.69^{*} (0.00)
FTSE 100	-3.33^{*} (0.00)	-2.71^{*} (0.01)	-2.97^{*} (0.00)	-4.22^{*} (0.00)	-2.71^{*} (0.01)	-3.45^{*} (0.00)
NIKKEI 225	-19.92^{*} (0.00)	-13.68^{*} (0.00)	-13.01^{*} (0.00)	-20.08^{*} (0.00)	-13.69^{*} (0.00)	-13.17^{*} (0.00)
Proxy: log range						
	Asymptotic test	Sign test	Wilcoxon test	Asymptotic test	Sign test	Wilcoxon test
	based on squared forecast errors			based on absolute forecast errors		
CAC 40	0.28 (0.71)	-1.55 (0.12)	-1.54 (0.13)	-0.29 (0.77)	-1.55 (0.12)	-1.75^{***} (0.08)
DAX 30	0.98 (0.33)	-9.30^{*} (0.00)	-3.78^{*} (0.00)	-0.44 (0.66)	-9.29^{*} (0.00)	-3.73^{*} (0.00)
DJIA	-6.0^{*} (0.00)	-8.78^{*} (0.00)	-3.73^{*} (0.00)	-6.33^{*} (0.00)	-8.74^{*} (0.00)	-3.71^{*} (0.00)
FTSE 100	-2.07^{**} (0.04)	-4.26^{*} (0.00)	-2.71^{*} (0.00)	-1.60 (0.11)	-4.26^{*} (0.00)	-2.17^{*} (0.00)
NIKKEI 225	-19.92^{*} (0.00)	-13.68^{*} (0.00)	-13.01^{*} (0.00)	-20.08^{*} (0.00)	-13.69^{*} (0.00)	-13.17^{*} (0.00)

Significance at the 1%, 5% and 10% levels is shown by *, ** and ***, respectively. The p-values are given in parentheses. A positive (negative) sign of the statistics implies that model 4 dominates (is dominated by) model 2. For the FTSE 100 index, we use the model 1, with and without dummies.

Table 12: Tests of equal accuracy: Model 3 versus Model 5

	Asymptotic test	Sign test	Wilcoxon test	Asymptotic test	Sign test	Wilcoxon test
Proxy: log absolute returns						
	based on squared forecasts errors			based on absolute forecasts errors		
CAC 40	−20.58*	−14.20*	−13.13*	−19.86*	−14.20*	−13.25*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
DAX 30	−5.46*	−9.29*	−3.93*	0.03	−9.30*	−3.78*
	(0.00)	(0.00)	(0.00)	(0.97)	(0.00)	(0.00)
DJIA	−4.09*	−7.23*	−3.48*	0.05	−7.23*	−1.05*
	(0.00)	(0.00)	(0.00)	(0.97)	(0.00)	(0.00)
NIKKEI 225	−9.10*	−3.09*	−2.69*	−3.31*	−3.10*	−2.69*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Proxy: log range						
	Asymptotic test	Sign test	Wilcoxon test	Asymptotic test	Sign test	Wilcoxon test
	based on squared forecasts errors			based on absolute forecasts errors		
CAC 40	−19.54*	−14.20*	−13.25*	−19.81*	−14.20*	−13.24*
	(0.96)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
DAX 30	−0.67	−9.29*	−3.78*	0.03*	−9.30*	−3.77*
	(0.50)	(0.00)	(0.00)	(0.98)	(0.00)	(0.00)
DJIA	−0.25	−7.36*	−3.51*	0.00	−7.35*	−3.44*
	(0.80)	(0.00)	(0.00)	(0.99)	(0.00)	(0.00)
NIKKEI 225	−9.10*	−3.08*	−2.69*	−3.31*	−3.09*	−2.71*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Significance at the 1%, 5% and 10% levels is shown by *, ** and ***, respectively. The p-values are given in parentheses. A positive (negative) sign of the statistics implies that model 5 dominates (is dominated by) model 3.

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